2019

Modeling grain storage outflow contamination levels, based upon input time series

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Modeling grain storage outflow contamination levels, based upon input time series

by

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Agricultural and Biosystems Engineering

Program of Study Committee:
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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2019

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ACKNOWLEDGMENTS

Earning this thesis has been a wonderful learning experience, but not without its trials. I would like to extend gratitude to my major professor, Raj Raman for his consistent guidance and encouragement. He has truly pushed my creativity for problem solving and my research abilities, all while allowing me to succeed. I also want to thank my other major professor, Bobby Martens for working hard to find a project I would excel at, giving me new paths to explore intellectually, and supporting me through this process. I want to show appreciation to my final committee member, Kurt Rosentrater, whom through our conversations about sustainability, engineering, and where the future is going has guided my path and made me confident in where I will be headed next.

The friends I have gained while studying at Iowa State has made my time here enjoyable and worthwhile. The ABE department welcomed me with open arms, giving me a space to fully realize my potential for academia, all while making this a fun and rewarding place to be. I especially want to thank Heather Tenboer, Suzanne Leonard, and Katie Taylor, all of which I made immediate friends with upon arriving at the university and without whom I would not have had such an amazing experience. I also want to thank Nurhaizan Mohd-Zainudin and Saxon Ryan for making my office experience wonderful and productive.

My support system from before coming to ISU, who always have my back and stretch my intellect with new challenges deserve recognition for this thesis as well. In particular, Hana Toribara, Stephanie Budrus, Kevin Kaifer, and Jake Knanishu are never wavering in their love and support of me. Without their consistent encouragement and ability get me back on track when I need it, I would not be where I am today.

I also want to thank my family. To my parents, who encourage me to follow wherever my heart leads me, thank you for unfailingly loving and encouraging me. To my younger sister Erica, thank you for reminding me of my abilities and giving me someone to be a role-model for. To my brother Paul, thank you for believing in me and always being there to listen when I need help with anything. I am truly thankful to have such an amazing family.

ABSTRACT

The main objective of this thesis was to use a modeling approach to simulate the concentration of grain contamination in an existing corn processing system. The majority of the plant input is GMO corn, which is processed into multiple end products. In addition to GMO corn, each year, the plant processes six 11-day runs of non-GMO corn. During these non-GMO runs, the overall GMO contamination of the products produced is required to be less than 0.9% per the 3rd party labeling organization Non-GMO Project standards. Each run takes in approximately 1,400 lots (1000 bu/lot), with a sub-sample from each lot being tested at entry into the plant for contamination. Lots are accepted or rejected based upon a contamination acceptance threshold set by the plant management. This thesis models the current system to assess its performance. After establishing the model for the existing system, this thesis explores the impact of operational changes that might reduce costs and increase confidence in the ability to meet 3rd party labeling requirements for non-GMO products. This thesis partially fulfills the Master of Science degree requirement in Agricultural and Biosystems Engineering.

The first chapter provides context and establishes the scope and reasoning behind the work. It includes a literature review summarizing the history of GMO production and regulation in the United States and incorporates history on legislation concerning the creation, commercialization, and consumption of GMO products, as well as market trends on desirable foods. It discusses the challenges in separating GMO and non-GMO supply chains, the testing methods for detecting GMO contamination, and concludes with the blending methods currently used to reduce costs in grain facilities.

The second chapter introduces a modeling approach for assessing the current system using a discrete time simulation. The program uses the time-series entry-point contamination levels provided by a cooperating entity grain processor to calculate the contamination in the storage system. The variability and periodicity of these data were explored, and the data were found to fit a beta distribution. Because of an assumption of perfect blending, the average contamination thereby computed within the storage system is also the contamination in the outflow from the storage system, which is subsequently sent to processing. We then used the model to examine how the acceptance threshold level impacts outflow contamination levels. This allowed us to explore the feasibility of accepting lower quality corn to be blended with higher quality corn, all while obtaining the required contamination percentages going into the processing system.

Chapter three examines a critical operational question, namely whether segregating the incoming lots by contamination into bin sub groups would improve the confidence in outflow contamination levels. This chapter proposes a method to determine how many bin sub groups should be used, the percentage of each bin sub group to put into the final flow to the mill, and a decision tree analysis on what to do when a particular bin sub group runs out. To increase the range of contamination levels beyond those provided in the real data, we generated beta-distributed artificial data sets to run through the model. This allowed an examination of how various numbers of bin subgroups, and operational rules, impact outflow contamination levels.

The thesis concludes with a summary of the findings and a discussion of potential future avenues of exploration.

CHAPTER 1. GENERAL INTRODUCTION

With the advent of Genetically Modified Organisms (GMOs) in agricultural production settings, there has been an ongoing debate about how GMOs impact the environment and human health. Utilizing GMOs in crops specifically have changed the way many farmers work, reducing pesticide use, increasing yield, and giving more confidence in the robustness of crops in instances of drought, floods, and diseases. Due to the advantages of GMOs, it has become increasingly difficult to separate the supply chain of non-GMO and GMO crops, especially in the United States, where major crops such as corn and soybeans are over 90% GMO (USDA ERS, 2018). However, consumers are demanding transparency in what foods they eat, which includes wanting to know if a certain product contains GMOs (Rock, 2014). Regulations in the EU have encouraged 3rd party labeling organizations to set a GMO contamination threshold for 0.9% (The Non-GMO Project-Standard, 2018). This 0.9% target is difficult to obtain as cross pollination, sharing transportation services, seed quality, and other supply chain issues can lead to the contamination of non-GMO plants (Devos et al., 2009).

A practice already commonly used by grain facilities is blending higher quality grain with lower quality grain in order to use as much grain as possible, while still achieving the required quality thresholds (Johnson, 2005). Linear programming and optimization methods have been used to analyze grain systems and to determine if blending would lower the production costs (Thakur, Wang, & Hurburgh, 2009).

This project uses a similar approach, but instead of analyzing a static system, assuming quantities of a certain quality of grain are always present in a system, a discrete time simulation model was created in MATLAB which takes time-series entry-point

contamination data and computes the contamination in the single, or multi-bin storage system, allowing prediction of the contamination in the outflow from the storage system. Assumptions are made based on guidance from a collaborating entity which provided the data, with their system in mind as the model was created. The model simulates the collaborating entity's current system, and then analyzes production runs to gain insight into how operation changes impact output contamination. We then give guidelines on how the system can be ran if the grain was segregated based on quality.

Objectives

The research objectives from this work are:

1. To model the current process
    - Analyze the quality parameter for accepting non-GMO into a mill
    - Acceptance thresholds
    - Evaluate critical parameters associated with current processes
2. To create a decision document for the collaborating entity to use to increase confidence in the output to the mill and reduce costs overall
    - Analyze how many sub groups to split the incoming grain into
    - Determine how much of each sub group should be used in the final flow into the mill
    - Compare the new proposed system to the current system
    - Investigate how changing means and variances into the system affect output

Thesis Organization

This thesis is organized into a general introduction which includes background and a literature review, two research articles, a general conclusion with future suggested work, as well as cited references and acknowledgments.

Literature Review

Sometimes called Genetically Engineered (GE) or just Genetically Modified (GM), GMOs have been under scrutiny all over the world since their inception. GMOs are products which have undergone changes to their DNA to create new characteristics. While GMO technology is relatively new, humans have been working to influence organisms for years through selective breeding, a process by which plants and animals with certain superior attributes are chosen and bred to continue this feature to their offspring (Balter, 2013). Examples include the domestication of wolves to dogs (vonHoldt et al., 2010) and corn which had more than a few kernels on each ear to those with multiple ears per stalk and increased kernels (Genetic Science Learning Center, 2013). However, it is not until recently through a process called recombinant engineering that humans were able to directly influence features in a much shorter time period- immediately after transferring the required gene. In 1973, Herbert Boyer and Stanley Cohen were able to extract a very specific gene from one organism and insert it in another. The gene transferred gave the recipient an antibiotic resistance that it did not have before (Cohen, Chang, Boyer, & Helling, 1973). After this procedure was discovered, the technology took off and continues to influence many aspects of American life.

Early history of GMO production started in 1974, just a year after Boyer and Cohen's discovery as the first animal was altered when Rudolf Jaenisch and Beatrice Mintz introduced foreign DNA to mouse embryos (Jaenisch & Mintz, 1974). In 1982, the FDA

approved Genentech's Humlin, a replica of human insulin as the first commercialized (Altman, 1982) GMO product. This was shortly followed by the first GMO plant in 1983, when a tobacco plant resistant to kanamycin was introduced (Lemaux, 2008). 1990 led to the start of GMOs in food or feed when the FDA approved Chymosin, a product used in cheese making (Post, 1990). The first whole food product approved was in 1994 when Calgene released Flavr Savr, a tomato whose ability to slow down the ripening process, giving consumers access to fresher- tasting and looking tomatoes (Bruening & Lyons, 2000).

With the advent of GMOs came concerns of how the technology could affect the environment and human health. Altering the very core of an organism had skeptics worried about the change in DNA not being able to be controlled- if scientists were able to change DNA in a laboratory, what stopped the gene from altering further after being released to the public? Would there be environmental impacts to farmland with new plants being introduced (Yang & Chen, 2016)? In 1974, Berg et. al published a white paper stressing their concerns about the potential biohazards of the technology. More specifically, they were worried about method of recombinant engineering (rDNA), which usually requires the use of a bacterium to clone the recombinant DNA molecules. A common bacterium to use is E. coli, and while E. coli is commonly found in the human body, what would be the effects of introducing this bacterium in a new way? Berg et. al realized their concerns, being just a year after Cohen and Boyer were successful, were based on the potential of risk rather than risk that had been demonstrated, and could lead to a stagnant in the advancement of the technology (Berg et al., 1974).

Even before the technology could take off, the National Institutes of Health (NIH) released guidelines which tightly regulated rDNA research, ensuring the US government had

a heavy hand in the process. As more developments in this field emerged, questions about how this could affect health and the environment continued, however the technology developed faster than answers about the risks, which have been continuously updated since 1976 (NIH Guidelines, 2016). Due to the potential risks associated with the new technology, the United States established a comprehensive committee, the Office of Science and Technology Policy (OSTP), to question how to regulate GMO technology in 1986 (McHughen & Smyth, 2007). The group decided to focus on the risk of the products being created, not necessarily the process by which the product was made. It was determined that current laws and regulations could be extended to protect against potential dangers of GMOs, with the corresponding governmental departments charged with the protection of the environment and as well as the health aspects of the technology. The coordinated Framework for Regulation of Biotechnology established the stance of the hazard being in the product, not in the process used to make the product. The risks were to be judged on the basis of 'same in-kind' as those presented by products not made with the rDNA process. The policy also gave the United States Department of Agriculture, the Environmental Protection Agency, and the Food and Drug Administration responsibility of the oversight of the products created by genetic engineering (McHughen & Smyth, 2007).

The 1970 National Environmental Act made the United States Department of Agriculture (USDA) responsible for investigating environmental impacts of decisions which could pose an environmental risk. OSTP decided this act allowed the USDA, specifically the USDA's Animal and Plant Health Inspection Service (APHIS), to govern GMOs in the United States' agriculture from pests and diseases. The department regulates specific aspects of all GMO plants before release, which includes import, field trials, and then finally,

commercial usage. The laws have since been updated and consolidated under the Plant Protection Act (PPA) of 2000. Under the PPA, once a plant has been deemed 'environmentally benign', it no longer needs oversight and can be released commercially (USDA, n.d.).

In 2018, the USDA finalized the National Bioengineered Food Disclosure Standard, which requires mandatory labeling on foods that are or may be bioengineered. The law comes into effect in 2020, with complete compliance by 2022. Foods with main ingredients containing 5% GMO contamination or greater, as determined by frequent DNA tests, will be labeled with "derived from bioengineering". Exceptions to this rule are made for food made with very 'refined' ingredients made from bioengineered crops, as usually refinement causes the end product to not contain detectable modified genetic material. Demands by United States citizens to understand more about where their food is coming from and to ensure they are making the correct decisions for their health influenced the decision to require labeling laws for GMO food products in America (Federal Register, 2018).

The Food and Drug Administration (FDA) has a plethora of experience working with GMOs, working from the beginning to ensure safety of food and feed made from GMO products. Under the FDA, the Center for Food Safety and Nutrition, as well as the Center for Veterinary Medicine examine new food and feeds, comparing proposed products with ones currently on the market. The FDA was responsible for approving the first commercialized GMO product, Humlin, and in 1992, issued a policy under the Food, Drug, and Cosmetic Act to regulate any new food or feed product (McHughen & Smyth, 2007). This policy works to ensure new allergens and toxins are not being introduced, as well as confirm comparable nutritional levels of GMO product with their non-GMO counterparts. If the product is not

significantly different, it does not require FDA approval to commercialize. Most proposed products do not require regulation, but all GMO foods and feeds currently available in the United States have gone under an FDA consultation (FDA, 2018).

The Environmental Protection Agency (EPA) is the final government group ensuring the safety of GMOs. In 1972, the Federal Insecticide, Fungicide, and Rodenticide Act gave the EPA authority to regulate pesticidal properties of plants. When GMOs were introduced, it was decided that the EPA would use this act to regulate any new pesticidal properties due to being genetically modified. The definition of properties in this case covers more than the recognizable GMOs which require a new, specific pesticide (i.e. Roundup Ready crop cultivars), but also those which are virus resistant, as well as those which 'produce' their own pesticides (McHughen & Smyth, 2007).

In 1994, the EPA issued its proposed regulations, which went into effect in 1995. The organization decided to determine 'low risk' plants, which include those which have properties that could be made with traditional selective breeding methods. Plants which would require evaluation are assed on a case by case basis, ensuring the plant is safe for public use. The EPA also requires information to ensure there are no gene flow issues- particularly if there is risk of spreading the pesticidal properties. The EPA is also charged with ensuring there are no adverse environmental impacts when the GMO plant is decaying from roots, leaves, pollen, etc. on its surrounding ecosystem (US EPA, 2015).

With the regulations for GMO plants being well defined, production of new crops has taken off in the United States. The FlavrSavr tomato, introduced in 1992 as the first genetically engineered whole food on the market, paved the way for innovations in the GMO food sector. Monsanto's NewLeaf potato was approved in 1995, with production starting

1996 (Federal Register, 1998). This was the first plant to be altered to produce a naturally occurring toxin, acting as a pesticide for the Colorado potato beetle. Also in 1995, Bacillus thuringiensis (Bt) corn was released into the market. Bt is a natural insecticide, used today by everyone from organic farmers to control crop-eating insects to the World Health Organization to kill mosquitoes, all while being safe for humans and other animals. (Bacillus Thuringiensis n.d.) With the ability to plant corn with innate pest resistance, farmers are able to reduce the amount of pesticides used after planting. Bt technology has been adapted to be useful for cotton crops and has grown considerably since 1995. In just 5 years, 35% of total US corn acreage and 19% of US cotton acreage was Bt varieties, and in 2018 this number grew to 82% and 91% respectively (USDA ERS, 2018).

Other uses for genetic engineering in plants were quickly developed after realizing their usefulness. In 1996, Monsanto created a genetically engineered soybean, used to tolerate herbicides. Being able to spray herbicide on a crop, killing the weeds in the area but not the crop itself allows farmers to greater control their fields (Wilkerson, 2015). These crops work in a variety of ways, including producing a new protein that will detoxify the herbicide, producing a physical barrier to prevent the herbicide from entering the plant, or changing the target protein in the plant so it will not be affected by the herbicide (Dyer, 2018). Currently, many types of crops are Herbicide Tolerant (HT) including soybeans, cotton, and corn. The technology has grown considerably from its introduction; in 2000, HT varieties made up 54% of soybeans, 46% of cotton, and 7% of corn acreage and today are present in 94%, 91%, and 90% of these crops respectively (USDA ERS, 2018). HT crops are not the only type growing in popularity in the United States- the number of GMO crops

approved for commercialization in the United States has increased since the 1992 to also include canola, alfalfa, sugar beans, apples, potatoes, papaya, squash.

In addition to enhancing the ease of growing plants, GMO crops are being created with either additional or increased nutritional quality. This is particularly useful developing countries where diets are primarily repetitive and cereal based (Farre et al., 2011). Golden Rice was developed in 2000, with boosted levels of vitamin A in an effort to combat blindness in areas prone to nutritional deficiency (Ye et al., 2000). Recently, the trend is moving towards multigene engineering- allowing plants to produce multiple nutrients not normally found in the crop. A corn variety was released recently in South Africa which successfully enhanced each kernel of corn with 169 times the amount of β-carotene, 6 times the normal amount of ascorbate, and double the amount of folate (Naqvi et al., 2009). Despite the benefits GMOs bring, including reduction in pesticide use, higher yields in crops, and reduction of greenhouse gases (Barfoot, 2005), Americans' concern with eating genetically engineered foods is growing. A third party verification organization, the Non-GMO project was created in 2007, with "the goal of creating a standardized definition for non-GMO products in the North American food industry." Since then, the 'butterfly' label has reached over 3,000 brands and 50,000 products, ensuring consumers know what they are eating. The demand for non-GMO foods is one of the fastest growing consumer trends in America (The Non-GMO Project Mission, n.d.)

A number of studies have recently been released, showing a growing trend in preference for non-GMO foods. Consumer Reports released a study in 2014 claiming over 70% of Americans do not want GMOs in their food, with over 40% actively looking for non-GMO labeling, and 92% of Americans wanting GMO usage labeled on food items (Rock,

2014) Just two years later in 2016, Nielsen released a survey saying that 54% of Americans are actively trying to avoid consuming GMO products (Nielsen, 2016). The Global Non-GMO Foods Market New Research Report from 2017 forecasted a growth of non-GMO foods of 16.23% from 2017-2021 (Reportlinker, 2017).

The USDA regulates GMO labeling as well. Currently, products that are labeled as 'Organic' must also be verified as non-GMO. Americans started demanding labeling, not only when a product does not contain GMO, but also when it does. In 2018, the USDA released mandatory labeling requirements for foods containing 5% or higher of GMO by weight of the main ingredient. This requirement reflects public demand to increase awareness on food sources (USDA AMS, 2019).

With the USDA's 2018 National Bioengineered Food Disclosure Standard (NBFDS) came pushback from the private Non-GMO Project labeling organization. Verification under the programs are different; with the NBFDS, "food in which any single ingredient contains more than 5% of a bioengineered substance, regardless of whether its presence is inadvertent or unintentional, is subject to disclosure." (Federal Register, 2018), while the Non-GMO project follow rules which reflect the European Union regulations of 0.9% or higher. The action thresholds are not the only difference in the standards. The US government will not be using the word GMO, instead either using a symbol or words stating "Derived from Bioengineering", or an electronic or digital link on the package, leading to information about the project. The different options for disclosure can be confusing to consumers if they not know what they are looking for. The NBFDS also allows for many exemptions including animal feed, pet food, and personal care products. Another exemption is given to products in

which GMO ingredient was highly processed as the DNA in these ingredients is no longer detectable (Non-GMO Project, 2019).

With the demand for labeling GMO products comes a grey area for private and government agencies. The gap between the Non-GMO Project's ingredient threshold at .9% being able to be labeled as non-GMO and the US government's threshold for labeling a product AS bioengineered being at 5% lends an opportunity for other labeling companies to provide a non-GMO label that would still fit government requirements, or force already established organizations to update their current labeling standards. Farmers will be more likely to grow non-GMO corn for a premium as the likelihood of too much cross pollination goes down. More companies will most likely start focusing on offering more products which do NOT have the bioengineered label, requiring new, segregated supply chains to accommodate this change in labeling.

Even with new labeling requirements in the United states, ensuring products are labeled properly is difficult. The verification to ensure ingredients are not exceeding 5% GMO is problematic, especially in farmlands and supply chains that are majorly GMO systems. When growing non-GMO crops, cross pollination is a major concern, especially when neighboring crops are GMO. Along the supply chain, using GMO systems could lead to higher levels of cross-contamination. Areas that could cause this cross contamination would include transportation (both rail and freight), storage (at the farm and the manufacturer), processing, and final product storage and packaging.

Devos et. Al (Devos et al., 2009) compiled a list of measures to ensure minimal mixing of non-GMO and GMO crops. These measures include: " *(i) the use of certified seed; (ii) spatially isolating fields of the same crop; (iii) implementing pollen barriers around*

fields; (iv) scheduling different sowing and flowering periods; (v) limiting carryover of GM volunteers into the following crop through the extension of cropping intervals; (vi) cleaning agricultural machinery and transport vehicles for seed remnants; (vii) controlling volunteers and wild/weedy relatives; (viii) applying effective post-harvest tillage operations; (ix) retaining records of field history; and (x) the voluntary clustering of fields." (Devos et al., 2009, p. 15) This list was created for the European Union, which has lower thresholds than the United states. The list is concluded with the realization that "*the lower the tolerance threshold, the stricter are the on-farm measures needed to meet labelling requirements."* (Devos et al., 2009, p. 15) According to the NFBDS, our thresholds are higher and require less stringent supervision than those in the EU, however, because the majority of our farmlands are GMO crops, keeping cross contamination to a minimum will be arduous.

Not only is it difficult to ensure crops are grown and segregated without contamination, but testing of GMO traces is troublesome as well. Testing can be inaccurate to a certain sensitivity, are subject to human error, and can be expensive to execute. There is currently no standard for testing and sampling methods can be incorrect and represent a small portion of the entire lot (Paoletti et al., 2006).

Testing for GMOs can be done with a few different methods, doing either a genetic analysis (DNA analysis) or an immunological analysis (protein analysis). The genetic analysis is done using a Polymerase Chain Reaction (PCR) test, which looks specifically for foreign DNA in the plant's genome. This test must be done in a laboratory and is highly sensitive and specific. There are 2 types of immunological analyses; a strip test which can be done in the field and is less accurate, and an Enzyme-Linked Immunosorbent Assay (ELISA) test, which is also done in a laboratory and provides greater certainty than the strip test. Due

to time restrictions as well as ease of the test, processing plants usually chose to utilize strip tests during receiving of grain, sending for a more accurate PCR test after processing is complete. Issues arise with requiring the use of the strip test before sending the sample off for a PCR test; the limit of detection for the strip tests is 0.1-1%, which is above the upper limit required by EU and Non-GMO project standards (GMO Testing, n.d.).

In addition to the limitations of the GMO testing techniques comes the issue of how to pull samples from lots for testing. When testing for GMO traces, sampling approaches would ideally reflect homogeneity, but practical limitations often prevent the sample from being an accurate represent the entire lot. Traditional testing is assumed to be random and characterized by a binomial distribution. A study done by European Food Research and Technology called the Kernel Lot Distribution Assessment (KeLDA) determined that GMO distribution is not random, meaning that normal samples taken for testing do not give a perfect portrayal of the lot, the samples showed a heterogeneous pattern when tested multiple times per lot (Paoletti et al., 2006).

With the uncertainty of GMO contamination in each lot, as well as the necessity to store grain in bins and pull from multiple bins at once when processing, blending to homogeneity to a certain extent is a reasonable approximation for what happens when entering a system. Many companies elect to segregate the incoming raw materials based on specific properties and blend among these quality groups to obtain an optimal attribute for the final product. Blending allows for raw materials which do not meet specifications to be mixed with those which have better than specification and average out to the quality level needed. This permits for companies to utilize as much material as possible, and sometimes buy lower quality and still fit within the needed parameters (Thakur et al., 2009).

Thakur et al. (2009) demonstrated blending a grain system, not only to meet customer specifications, but also reduce the number of bins used for traceability reasons. The fewer bins utilized minimizes food safety risks in case of a recall or other quality issue. They elected to use a multi-objective mixed integer programing (MIP) model, using minimization of bins and minimization of customer discounts (given if specifications are not met) as their objectives. The model gave the elevator a set of blending options, Johnson (2005) analyzed grain blending under the assumption that measured quality attributes and then assessed the overall quality of grain out of the system after sorting and blending. The paper then developed an optimization model which incorporates the uncertainty of quality at an overall level and how this would affect blending decisions. In this particular scenario, the goal was to obtain a certain level of protein, as certain protein will give either premiums or discounts. The uncertainty comes from not only the initial testing of the grain going into the system, but also how does blending both within the bin as well as on output (using more than 1 bin with certain quality attributes) influence the final quality. The process involved drawing six samples from a mixed normal distribution from the region they were testing. The samples were then split into a high protein group and low protein group, with 3 samples in each. This was repeated 100 times to represent the expected returns on blending given the distribution of protein within the available lots. This was compared to a simulation where the lots were not split and just pulled from randomly. In all cases, sorting the grain before entering the system increased profits.

Even with the studies being done for grain blending, there is currently no work being done on quality attributes of a continuous process. Modeling lots going into a system as they are being pulled out to be put into the process provides a unique opportunity to test not only

how quality parameters change as new corn is introduced into the system, but then we are also able to provide a sorting and blending proposal to further improve confidence in the final product's quality. This work focuses on modeling the current system and how acceptance thresholds for GMO contamination can be changed without sorting and blending, and then a proposal for sorting and blending corn upon receiving.

CHAPTER 2. MODELING GRAIN STORAGE OUTFLOW CONTAMINATION LEVELS: INTERACTIONS BETWEEN INFLOW MEAN AND VARIANCE, ACCEPTANCE THRESHOLDS, AND OUTFLOW CONTAMINATION LEVELS

Introduction

The collaborating entity processes GMO and non-GMO products. Currently, the non-GMO product is ran on a processing system normally used for GMO product production. These production runs last for 11 days and are scheduled in advance. The collaborating entity does six 11 day non-GMO runs a year, with potential to increase this business if needed.

To ensure limited cross contamination from running this product on their normal GMO processing system, the non-GMO corn is segregated into clean bins and the processing system is cleaned out thoroughly before the non-GMO corn is allowed into the system. Non-GMO lots come in to the processing facility and are tested for GMO contamination before going into the bin storage system. GMO contamination comes from a multitude of places, including impure seeds, cross pollination with GMO crops, and contamination along the supply chain including storage bins, trucks, and processing systems. When running non-GMO production runs, the collaborating entity has a contamination upper limit of 0.9% GMO, which is consistent with 3rd party labeling company Non-GMO Project standards.

With the potential for GMO contamination being ever present, figuring out what to do with corn which is tested at input above the 0.9% threshold can become an issue. One method is to blend purer corn with higher contaminated corn, averaging out to the desired quality. If this method is chosen, the collaborating entity must ensure that the corn coming out of the milling process has been blended enough to reach below 0.9% contamination. Non-GMO corn comes into the bin storage system in lots, which is then stored in bins, or sometimes is transferred between bins depending on storage capability, and then the mill

pulls the non-GMO corn from multiple bins during processing to meet throughput requirements. Blending between lots happens during all of these grain transfers and thus perfect blending of accepted lots at exit of the system is assumed.

The assumption of perfect blending allows the collaborating entity to use corn with higher contaminated percentages that will be blended with lower contaminated corn. As lots come into the system via truck deliveries and out of the system via processing to the mill, the overall contamination level will change depending on the quality of corn being delivered. Understanding what the overall contamination percentage is within the system allows the collaborating entity either accept or reject higher contaminated corn and be confident in being below the 0.9% contamination threshold. This project takes timestamped contamination data of incoming loads from actual runs of non-GMO corn and simulates a discrete time process to understand how the system responds when different contamination levels are added and taken out.

While this exact process is unique to the collaborating entity, the methods developed for this research can be used in other grain processing plants to create confidence in their non-GMO processing systems. Being able to use higher contaminated corn can lead to lower costs per unit of production, as well as utilization of corn that may not have been pure enough by with no blending. The methods used here can also be utilized for other quality metrics of grain processing systems.

Literature Review

Sometimes called Genetically Engineered (GE) or just Genetically Modified (GM), GMOs have been under scrutiny all over the world since their inception. GMOs are products which have undergone changes to their DNA to create new characteristics. While GMO technology is relatively new, humans have been working to influence organisms for years

through selective breeding, a process by which plants and animals with certain superior attributes are chosen and bred to continue this feature to their offspring (Balter, 2013). Examples include the domestication of wolves to dogs (vonHoldt et al., 2010) and corn which had more than a few kernels on each ear to those with multiple ears per stalk and increased kernels (Genetic Science Learning Center, 2013). However, it is not until recently through a process called recombinant engineering that humans were able to directly influence features in a much shorter time period- immediately after transferring the required gene. In 1973, Herbert Boyer and Stanley Cohen were able to extract a very specific gene from one organism and insert it in another. The gene transferred gave the recipient an antibiotic resistance that it did not have before (Cohen et al., 1973). After this procedure was discovered, the technology took off and continues to influence many aspects of American life.

Early history of GMO production started in 1974, just a year after Boyer and Cohen's discovery as the first animal was altered when Jaenisch and Mintz introduced foreign DNA to mouse embryos (Jaenisch & Mintz, 1974). In 1982, the FDA approved Genentech's Humlin, a replica of human insulin as the first commercialized (Altman, 1982) GMO product. This was shortly followed by the first GMO plant in 1983, when a tobacco plant resistant to kanamycin was introduced (Lemaux, 2008). 1990 led to the start of GMOs in food or feed when the FDA approved Chymosin, a product used in cheese making (Post, 1990). The first whole food product approved was in 1994 when Calgene released Flavr Savr, a tomato whose ability to slow down the ripening process, giving consumers access to fresher- tasting and looking tomatoes (Bruening & Lyons, 2000).

With the advent of GMOs came concerns of how the technology could affect the environment and human health. Altering the very core of an organism had skeptics worried about the change in DNA not being able to be controlled- if scientists were able to change DNA in a laboratory, what stopped the gene from altering further after being released to the public? Would there be environmental impacts to farmland with new plants being introduced? (Yang & Chen, 2016). In 1974, Berg et al. published a white paper stressing their concerns about the potential biohazards of the technology. More specifically, they were worried about method of recombinant engineering (rDNA), which usually requires the use of a bacterium to clone the recombinant DNA molecules. A common bacterium to use is E. coli, and while E. coli is commonly found in the human body, what would be the effects of introducing this bacterium in a new way? Berg et. al realized their concerns, being just a year after Cohen and Boyer were successful, were based on the potential of risk rather than risk that had been demonstrated, and could lead to a stagnant in the advancement of the technology (Berg et al., 1974).

Regulations on GMO food products have stemmed from this potential risk rather than demonstrated risk. The United States has had regulations on GMO commercialization and growth, but this did not include food labeling requirements which some other places in the world had in place (the EU is an example of this). However, in 2018, the USDA finalized the National Bioengineered Food Disclosure Standard (NBFDS), which requires mandatory labeling on foods that are or may be bioengineered. The law comes into effect in 2020, with complete compliance by 2022. Foods with main ingredients containing 5% GMO or greater, as determined by frequent DNA tests, will be labeled with “derived from bioengineering” (National Bioengineered Food Disclosure Standard, 2018).

Though the United States now has a labeling law being put into place for genetically modified foods, there are third-party labeling organizations already established to give consumers the option of choosing non-GMO foods if they want to. One such organization, the Non-GMO project was created in 2007, with "the goal of creating a standardized definition for non-GMO products in the North American food industry." Since then, the 'butterfly' label has reached over 3,000 brands and 50,000 products, ensuring consumers know what they are eating (The Non-GMO Project- Mission, n.d.). The qualifications for being considered a non-GMO product are more stringent than the laws put in place by the NBFDS, with corn ingredients in particular having less than 0.9% GMO DNA. This quality standard is one many American food companies strive for, especially because of the growing demand for non-GMO products.

A number of studies have recently been released, showing a growing trend in preference for non-GMO foods. Consumer Reports released a study in 2014 claiming over 70% of Americans do not want GMOs in their food, with over 40% actively looking for nonGMO labeling, and 92% of Americans wanting GMO usage labeled on food items ((GMOS in Food - Consumer Reports, n.d.). Just two years later in 2016, Nielsen released a survey saying that 54% of Americans are actively trying to avoid consuming GMO products (Nielsen, 2016). The Global Non-GMO Foods Market New Research Report from 2017 forecasted a growth of non-GMO foods of 16.23% from 2017-2021 (Reportlinker, 2017).

With the trend for more non-GMO products, companies are working to add such products to their portfolios. However, ensuring products do not have higher than the minimum 0.9% GMO contamination for the Non-GMO Project label is difficult as many

ingredients, including those which are specifically grown as non-GMO, have GMO strands in them.

With the number of farm fields growing GMO products (leading to cross pollination), as well as the grain supply chain being used for GMO products, adulteration from GMO plants leads to required testing of crops grown as non-GMO to ensure limited contamination. Testing methods to determine contamination vary in accuracy and speed. The method used for this paper's purposes is a 'Quick Test', which is a strip test that can be done in the field and is less accurate than some methods which take much longer to process. The quick test has a sensitivity limit of detection of 0.1 to 1 percent, giving variation to the accuracy of the test. Samples of the final product is sent to an offsite lab which offers greater capabilities to ensure contamination levels less than the 0.9% required (GMO Testing n.d.).

The growth of non-GMO demand has led processing companies to pay more for lots of non-GMO crops. To incentivize farmers to carefully grow, store, and transport ingredients to their processing facility, companies are paying farmers premiums based on how pure their raw ingredients are when arriving to the processing facility. In order to maximize profits and use higher contaminated corn, blending the lots coming in allows for raw materials which do not meet specifications to be mixed with lots which are purer than specification requires. The result average out to the quality level needed. This permits companies to utilize as much material as possible, and sometimes buy purchase corn with higher contamination levels and still maintain the required parameters.

When a large quantity of corn enters a processing system, it is not stored and processed in individual lots. The grain is stored in bins, which, depending on the bins shape and capacity, will flow out of the bin blending as it does so. Many times, corn is pulled from

multiple bins at a time, adding another form of blending. Finally, as the corn is processed in the mill, mixing occurs. Because of these factors, an overall average GMO percent contamination based on the corn already in the storage system can be calculated. As corn arrives in a storage system, calculating this overall contamination average can be used as a rule of thumb to check if the overall contamination is getting too high. Based on this calculation, lots can be accepted or rejected with higher or lower contamination levels. The contamination value at which corn enters into the process is called the acceptance threshold and is the basis for this paper.

Materials and Methods

To assess the contamination percentage of the system as lots enter and exit the system, we created a discrete time model using lot-by-lot contamination levels as an input. Each lot is assumed to have equal size – an assumption well supported by delivery truck capacity. The model uses simple mass-balance mixing approaches to track contamination levels inside the bin system, and the output of the model is a string of contamination levels corresponding to batches shipped out to downstream parts of the plant. The model allows for varying thresholds to be applied to the grain accepted into the storage system.

For purposes of this paper, acceptance threshold is the highest percent contamination allowed into the storage system to be blended with the corn already present. Corn entering the bin storage system will be called input. After exiting the bins to be processed, the contamination level in the output from the bin storage system has to be less than 0.9 percent. Due to the complexity of the milling processing system, we decided to assume perfect blending within the bins and the desired overall contamination to the mill is what is being measured. The term ‘output’ is the product going into the mill. Third party labeling cutoff

for acceptable GMO contamination percent is 0.9 percent, which is what this model will be using as its success criteria.

A discrete time model of the storage system was implemented in MATLAB. Each timestamped lot comes in sequentially, is accepted or rejected, and then enters the bins if accepted. While the number of lots coming into the plant is different for each run, generally corn is accumulated for a day without being pulled into the mill processing system. After this time period, corn is still accepted, but then lots are go out to processing at the same rate. This happens for ten days. On the eleventh day the system runs on storage without receiving new shipments. Each run has approximately 1,400 lots that come in during the 11-day period.

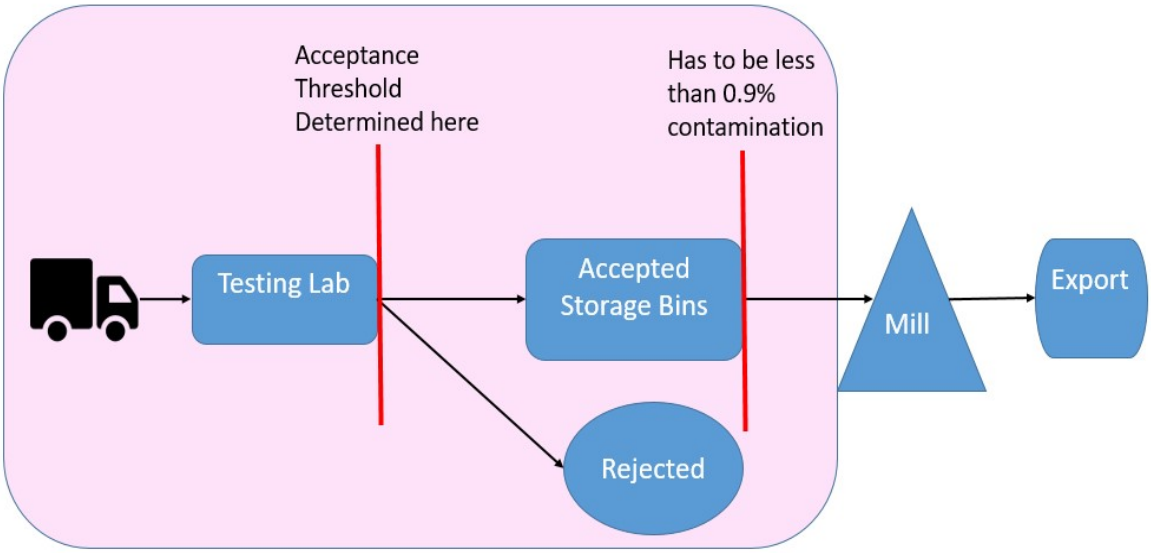

Figure 1 Overview of mill, including bin storage system (central), input threshold check (left red line), output contamination level (right red line). Light red area represents storage, measurement, and decision system which the model simulates

Figure 1 above shows the process as corn enters the storage system. As corn arrives at the processing facility, a probe is used to extract a sample from the truck to take to the testing lab to determine the percent GMO contamination of that lot. A commercially available quick

test is used to determine the contamination level of each lot. The quick test involves the following steps: (1) grind approximately a ½ gallon of corn through a 20-mesh sieve and mixed thoroughly, (2) 240-g sample is weighed out and added to a quart sized container, (3) 360 +- 2ml of tap water is added and shaken vigorously for 30 seconds, (4) the sample settles for at least 30 seconds and then liquid is drawn off, (5) 20ml of the liquid portion of the settled sample is put into a sample cup and allowed to settle for 30 seconds, (6) a quick test strip is added into the sample, which develops for 5 minutes before being interpreted, and (7) the test strip is placed into a strip reader, with results displayed on a computer. This method yields the percent concentration of nine different potential foreign DNA strains by weight. The sum of these percentage contamination levels represents the total GMO contamination of the sample.

After the contamination level is determined (hereby denoted as c_n, with n being the sample number), the lot is either accepted or rejected based on the value of c_n relative to an acceptance threshold value. In this modelling work, the nominal acceptance value of 2.5 percent was used. Accepted corn enters the storage system and is comingled with the existing corn. Mixing of the lots happens naturally within the entire system as corn is transferred from bin to bin, as corn moves to the processing system, and when corn is in the processing system. Due to these mixing events that are inherent to the bin storage system, we assumed perfect blending in the model. The assumption of perfect blending implies that output contamination percentages are equal to the mass average contamination of the inflow, per the following equation:

$$BC = \sum \frac{C_n}{bin_{vol}}$$

(Equation 1)

Where BC is the overall contamination of the storage system and bin_{vol} is the volume of the loads in the system, and c_n is the contamination of the loads in the system. For the first day, the mass contamination percentage of the storage system is just equal to the average of the inputs into the bins. In order to normalize the contamination added to the storage system, the following set of equations is used:

$$m_{tot} = m_{tot} + V_n \times C_n$$

(Equation 2)

$$bin_{vol} = bin_{vol} + V_n$$

(Equation 3)

$$C_{tot} = \frac{m_{tot}}{bin_{vol}}$$

(Equation 4)

Where m_{tot} is the total mass of contaminated grain in the storage system, V_n is the volume of the lot coming into the bin system, c_n is the contamination of the lot entering the bin system, and c_{tot} is the contamination of the entire bin system assuming perfect blending.

Once this accumulation period is completed, the system starts feeding into the mill as well as accepting new lots. The output contamination going to the mill is calculated using the following equations:

$$m_{tot} = m_{tot} + V_n \times C_n - C_{tot} \times V_{lot}$$

(Equation 5)

$$C_{tot} = \frac{m_{tot}}{bin_{vol}}$$

(Equation 6)

The new m_{tot} equation accounts for the output to the mill, with V_{lot} representing the volume of grain going to the mill. In our case, V_{lot} is the same as V_n as the system is at steady state after accumulating for a day. As new lots are accepted into the system, the contamination changes, resulting in a new contamination output percentage. This output value was collected and analyzed to see the values going into the milling system over the entire run.

Once the system was set up to see the output contamination going into the milling system, we decided to see if we could increase the acceptance threshold to allow lower quality corn to be used in processing, while still being lower than the 0.9 percent contamination level required for corn going to the mill. To do this, the above process was ran for multiple acceptance thresholds, starting at 2.0 percent through 10 percent at 0.25 percent intervals. All instances when the contamination to the mill went above 0.9 percent were recorded. At the end of each threshold interval, the average contamination to the mill was calculated, as well as the number of rejected lots. As can be imagined, as the acceptance threshold increased, the number of rejected lots decreased.

Data

The collaborating entity provided nine GMO contamination data sets, each from a separate production run, and ranging in size from approximately 1,100 to 1,700 data points. Due to cross pollination, seed quality, and supply chain contamination, each run had a different distribution of grain contamination coming into the system. Visualizing the concentration data in a histogram (Figure 2) shows that incoming lots are not normally distributed for several reasons, including the data's non-negativity and maximum value (100%) constraints.

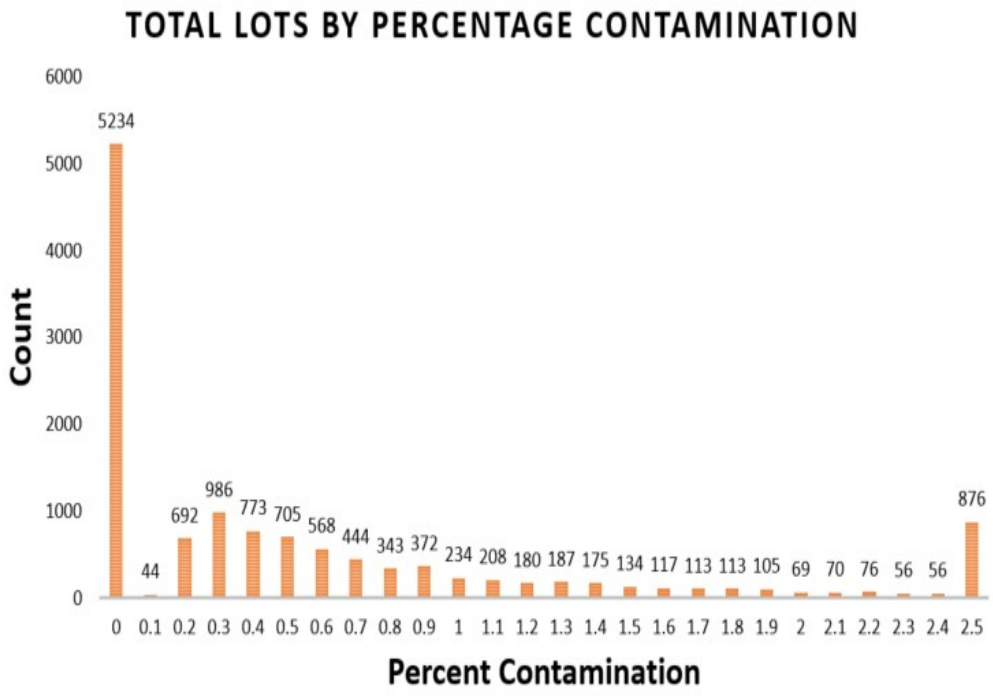

Figure 2: Lot by percent contamination of all data given by cooperating entity

The distributions were fit as beta distribution (Upton & Cook, 2014). Beta distributions are defined by parameters alpha and beta, which impact the shape of the distribution. The alpha and beta parameters for each of the nine data sets provided by the collaborating entity were determined using the *finddist* function in MATLAB (Mathworks, 2009).

We visualized the contamination data to look for patterns (Figure 2 below). Visual inspection did not suggest periodicity. Still, to ensure none, autocorrelation analyses were conducted for each data set via MATLAB's *autocorr* and *parcorr* functions (Mathworks, 2006). The visual results and those from *autocorr* and *parcorr* on one set of data are presented in Figure 3. The functions were ran on all data sets with similar results (data not shown). Essentially, no periodicity was found in any of the contamination data sets.

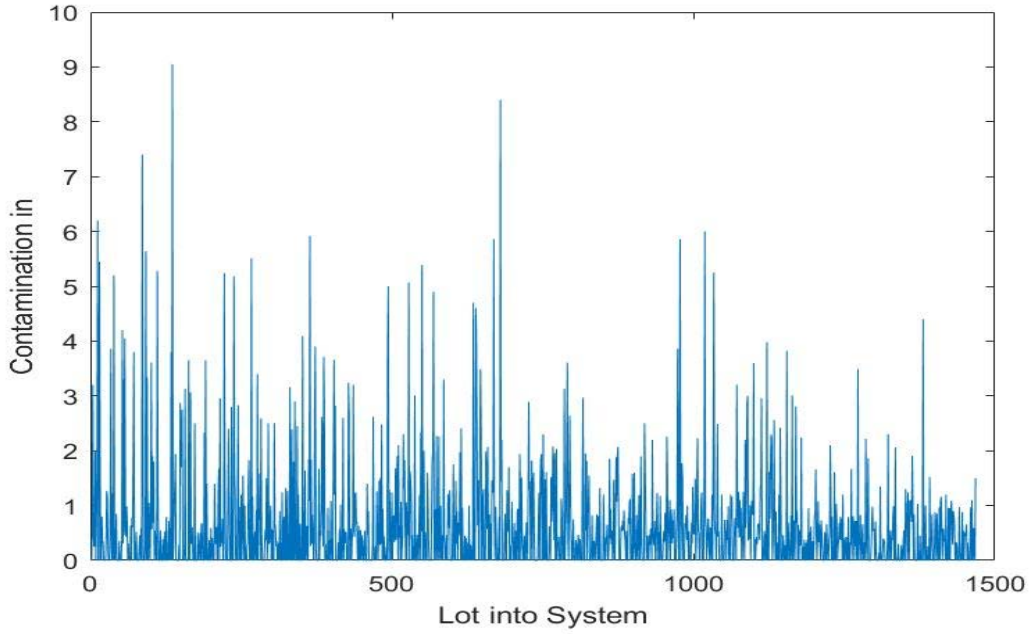

Figure 3 Contamination profile of lots into the system with normal average contamination

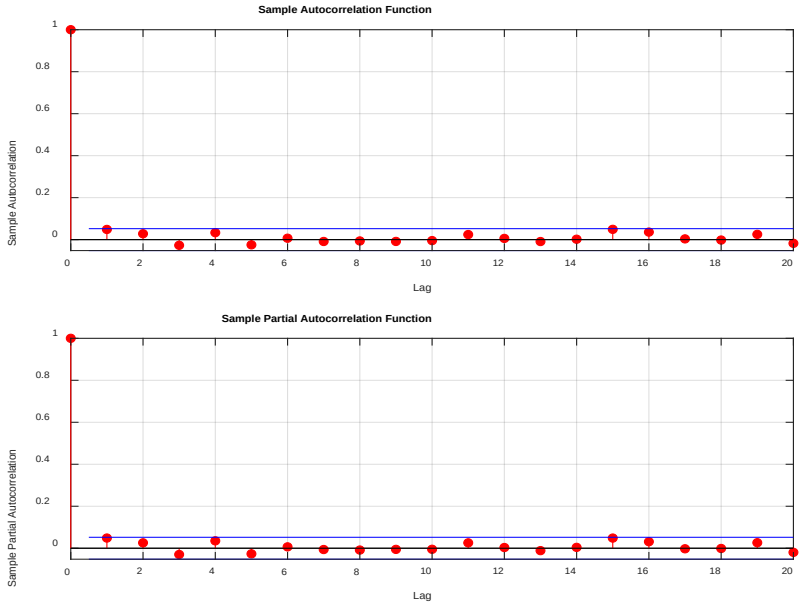

Figure 4 Autocorrelation and Partial Autocorrelation for an average contamination run

As can be seen above, the average month does not show signs of partial or full autocorrelation. We checked for autocorrelation as sampling testing methods could lead to periodicity in the data.

We also looked at the other available data sets for autocorrelation and partial autocorrelation. The low contamination month results are shown in Figures 5 and 6.

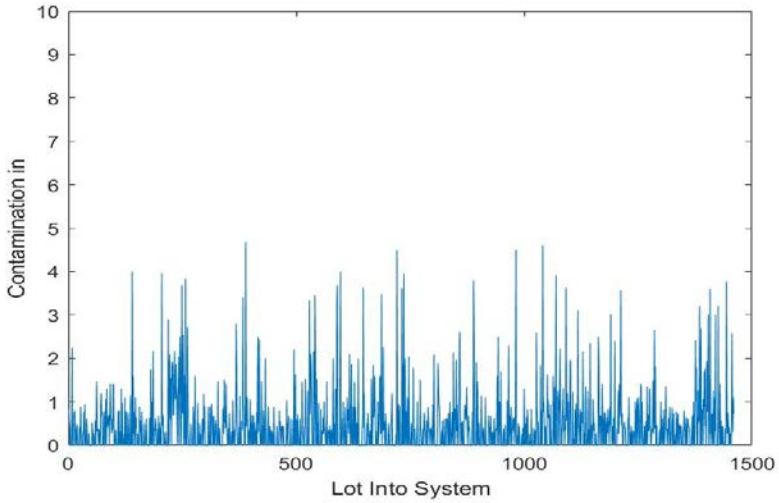

Figure 5 Contamination profile of lots into the system with a low average contamination

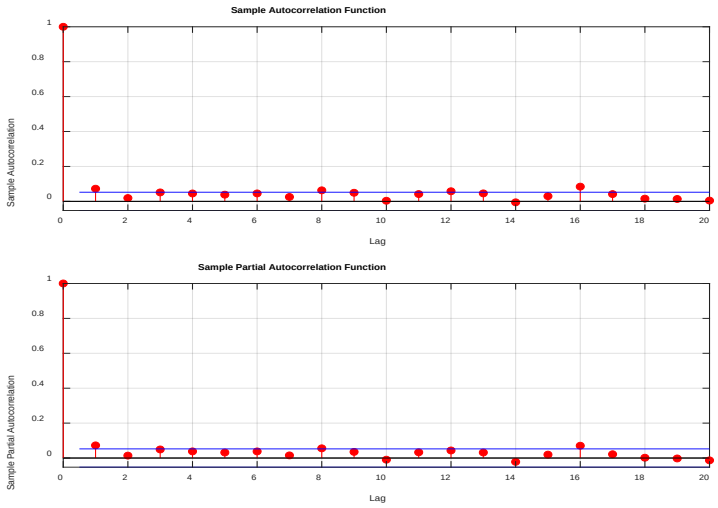

Figure 6 Autocorrelation and Partial Autocorrelation for an low contamination run

An average and low contamination run were used to check the validity of changing the acceptance threshold. There were nine sets of data available, each with different numbers of lots going into the run, different GMO contamination level averages and standard deviations, and different acceptance thresholds. Table 1 shows the statistical data for each data set, with any data above the 2.5 percent (not accepted into the system) excluded.

Table 1 Data sets provided by the collaborating entity

Data Set	Total lots	Rejected lots	Average Contamination	Standard Deviation	Alpha parameter	Beta parameter
1	1294	77	0.56	0.93	0.27	39
2	1108	112	0.71	1.21	0.31	35
3	1254	309	0.83	0.69	0.46	27
4	1710	155	0.42	0.58	0.25	39
5	1468	128	0.46	0.59	0.26	40
6	1698	69	0.4	0.51	0.27	53
7	1537	104	0.47	0.57	0.28	43
8	1460	55	0.38	0.52	0.26	55
9	1400	68	0.37	0.51	0.25	47

From the above data sets, we chose to analyze a normal contamination average (set 5, hereby average contamination) and the lowest contamination average (set 8, hereby low contamination).

Results

Tracking the contamination as it goes to the mill under a perfectly blended system allows us to analyze the final product going into the mill, with the intent of never crossing the 0.9 percent contamination requirement. The first model was ran with a 2.5 percent acceptance threshold for average and low contamination runs. Running the simulation under

these circumstances lets us determine if we are meeting the 0.9 percent contamination requirement. The table below summarizes the data sets used in these simulations:

Table 2 Data Sets Used in Simulation Analysis

Data Set	Total lots	Rejected lots	Average Contamination	Standard Deviation	Alpha parameter	Beta parameter
Average	1468	128	0.46	0.59	0.26	40
Low	1460	55	0.38	0.52	0.26	55

Using the data sets above, the simulation was ran with a 2.5 percent acceptance threshold. The average contamination in the system was calculated, and the output going to the mill was recorded using this average. Figure 7 below shows the output of the average, and low contamination runs into the mill from the bin system:

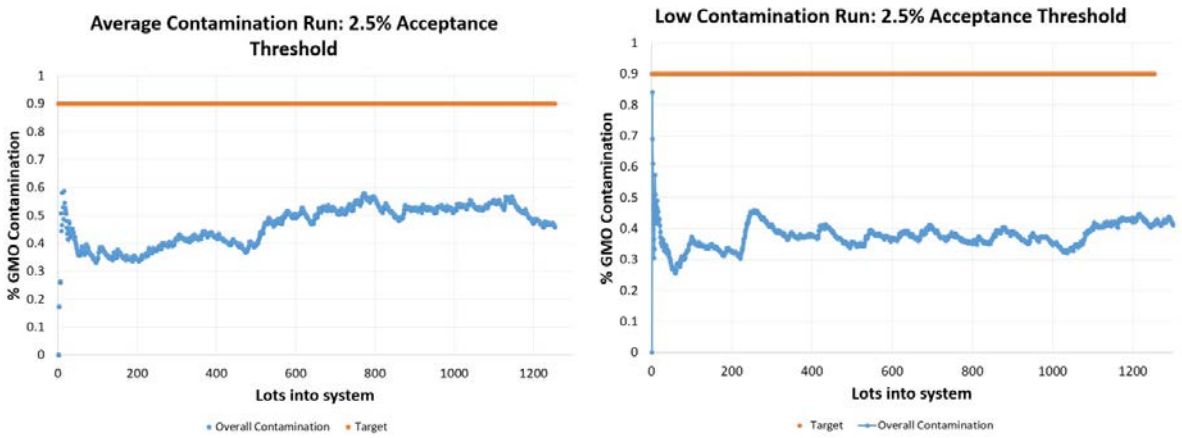

Figure 7 Calculated GMO contamination going into the mill with a 2.5% acceptance threshold during average and low contamination runs

Table 3 Statistics for simulation for average and low contamination runs

Run	Average Contamination %	Max Contamination %	Min Contamination %	Standard Deviation
Average	0.45%	0.59%	0.33%	0.069%
Low	0.38%	0.46%	0.30%	0.031%

As can be seen in Figure 2, the average and low contamination runs were below the 0.9 percent contamination level requirement for the entire run. However, the low contamination run had less than half of the standard deviation than the average run. With less variation of the grain going into the run, the less likely higher contamination corn are found. Both of these figures allow the plant to be 'confident' in running with a 2.5 percent acceptance rate, with the possibility of accepting even higher contaminated corn.

After seeing how the average contamination of the mill was so low during the average and high runs, the acceptance threshold was changed to allow higher contaminated corn into the system while remaining under the 0.9 percent contamination requirement. This allowed for lower rejection rates and lower costs per lot out over the entire system. The system was tested to a 10 percent acceptance threshold, due to the potential of higher contaminated corn throughout. So, the simulations were ran for all acceptance thresholds from 2 to 10 percent in 0.25 percent increments. We tracked the average contamination going to the mill as well as the number of rejected lots for each acceptance threshold. Figure 8 below shows the results for changing the acceptance threshold for the average, and low contamination runs:

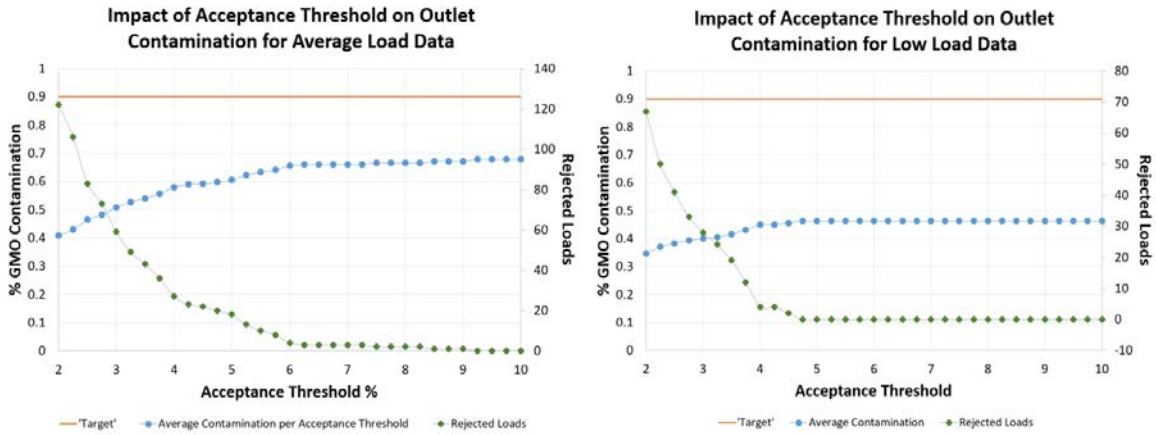

Figure 8 Average percent GMO contamination and number of rejected lots for acceptance threshold percent of 2 to 10 percent for low and average contamination runs

Table 4 Statistics for simulation for average and low contamination runs ranging under new acceptance thresholds

Run	Min Contamination %	Max Contamination %	Min Rejected Lots	Max Rejected Lots
Average	0.41%	0.68%	0 at 9.25% acceptance	122 at 2% acceptance
Low	0.35%	0.46%	0 at 4.75% acceptance	67 at 2% acceptance

Increasing the acceptance threshold in average or low contamination cases allows the system to accepted higher contaminated corn and still be well below the 0.9 percent required threshold. Because corn with greater purity normally costs more, blend corn with less contamination with higher contaminated corn reduces costs and results in fewer rejected lots.

Discussion

The research described above results in questions related the amount of management needed to ensure necessary contamination percentage out of the bin storage system to the mill. The average and low contamination runs were much lower than the necessary 0.9 percent

threshold. However, if the plant did receive higher contamination lots, there is potential to go above the 0.9 percent threshold, meaning more intense management, including the potential of changing the acceptance threshold in the middle of the run. This model gives an approximate contamination percentage going to the mill but does not account for the risks of processing sections that are not perfectly blended. If, for some reason, a batch of highly contaminated corn is not properly blended, the output into the mill could be higher than the necessary contamination threshold. When considering the maximum acceptance threshold, the low and average contamination runs lead to many questions about opportunities to lower costs and rejection numbers. While there is still the risk of high-contaminated hot spots and the reliability of the testing method, the model showed promising contamination averages headed from the bins into the mill.

Knowing where the corn is within the system also leads to greater confidence in blending capabilities. Currently, we are assuming a perfect blending system within all the bins, but this leads to potential hot spots. Segregating the highly contaminated corn to slowly blend with purer corn would allow the plant to understand exactly when that corn is going into the mill.

Conclusion

Being able to track the average of the contamination going into the mill allows for greater confidence in adherence to the required contamination threshold. This also opens the doors for accepting higher contamination corn, potentially at a lower price. The assumption of perfect blending and addressing the variability of the quick test are limitations of this study. Understanding the difference between the quick test and the more reliable and expensive PCR test would allow validity or not in this conservative acceptance threshold.

With the passing of the National Bioengineered Food Disclosure Standard, this study becomes even more important. The market for non-GMO corn will most likely grow, just to avoid being labeled as a GMO product. With the regulations only requiring a 5 percent or lower contamination level, the potential to blend even lower quality corn can lead to greater costs savings, potentially leading to lower costs for production companies. Another benefit of the NBFDS is the potential to have two tiers of non-GMO products; those which would fit the Non-GMO project requirements and one to fit the NBFDS. If production companies have the capacity to separate ingredients when they come into the system into tiers, rejected lots can be reduced, and confidence in the contamination going into the processing system can be increased.

CHAPTER 3. MODELING GRAIN STORAGE OUTFLOW CONTAMINATION LEVELS: IMPACT OF STORAGE SEGREGATION AND MIXING RULES ON OUTFLOW CONTAMINATION

Introduction

The collaborating entity processes non-GMO corn in the same system as their GMO corn start production. The collaborating entity has six 11 days non-GMO receiving and processing events per year. In order to reduce cross contamination of the GMO and non-GMO corn, the non-GMO corn is segregated into clean bins and the processing system is cleaned out from the GMO run before starting the non-GMO run. The collaborating entity has works hard to ensure the final contamination of the product is below 0.9 percent GMO, a standard given by the 3rd party labeling company (The Non-GMO Project- Standard, 2018)

Upon arrival to the plant, trucks deliver lots of non-GMO corn, which come in to the processing facility and are tested for GMO contamination before going into the bin storage system. Placement of lots into the storage system is not determined by any particular method, with the corn going to wherever has the most space or is most convenient for the driver. There are multiple bins available. Though the plant has precautions in place to limit the cross contamination within their own system, outside sources of contamination means that lots do not show up at the plant completely pure. Contamination of corn with GMO strands can come from a multitude of sources, including impure seeds, cross pollination with GMO crops, and contamination along the supply chain including storage bins, trucks, and processing systems.

With the potential for GMO contamination being ever present, figuring out what to do with corn that comes in above the 0.9% threshold can become an issue. One method commonly used in the grain industry for other quality attributes such as moisture and protein

is to blend incoming lots to average out to the desired quality. Doing this allows the facilities to buy lower quality lots of grain at lower prices which is blended with more expensive, higher quality lots. The result meets the necessary desired quality. In order to confidently blend the grain, facilities segregate lots based on the quality attribute, and mix the segregated lots in predetermined quantities. If blending and segregation is utilized in order to use higher contaminated corn, the processor need to ensure that the corn coming out of the milling process has been blended enough to not exceed the 0.9 percent contamination level.

In chapter 2, perfect blending of the non-GMO corn was assumed. The contamination going to the mill is the average of the contamination of all of the lots in the system. This assumption, however, can lead to risks of lots of higher contaminated corn being processed if not blended properly with lower contaminated corn. Due to the risk of processing the higher contaminated corn without proper blending, the collaborating entity seems to act conservatively when accepting higher contaminated corn into their systems, rejecting lots which do not meet a specific contamination acceptance threshold. The plant aims to keep the overall contamination average in the bin storage system below the 0.9 percent contamination requirement. Doing this means that higher contaminated corn, which is usually bought at a lower price, is rejected from the non-GMO processing system.

The purpose of this paper is to model what would happen if the plant adopted simple blending practices. This is an assessment of whether or not segregation and blending would allow the plant to accept higher contaminated corn, reducing the costs of production and increasing the confidence in achieving the required contamination percentages going into the mill. In the segregated model, instead of one common bin storage area, the system is divided into bin sub groups (BSGs). To assess the value of segregation and blending, one must

determine how many BSGs to use, the contamination ranges for each BSG, the amount of each BSG which will go into the mill, and implications of running a BSGs empty or low.

While this exact process is unique to this collaborating entity's production facility, the methods developed here can be used in other grain processing plants to create confidence in their non-GMO processing systems. Modeling this system leads to both an increase in confidence in the contamination levels going into the mill, but also a reduction in production costs as lower quality corn is able to be utilized.

For this chapter, a system with 1 BSG (i.e., base case) and then 3 BSGs were modeled using a discrete time simulation similar to that developed and described in Chapter 2 of this thesis. An assumption used for these BSGs is perfect blending within each bin. Perfect blending both simplifies calculations and is supported by the collaborating entity's input. We create artificial data sets which are statistically similar to the actual data provided by the collaborating entity, but which could have more extreme contamination, to challenge the system. We then evaluate the simulated system performance.

Literature Review

Blending is a practice used by many grain processing systems to obtain quality attributes such as moisture and protein. Companies will test for these characteristics upon entry, decide if the grain meets certain minimum quality thresholds, and then segregate grain based on these criteria, usually paying more for higher quality grain. To reduce costs, this higher quality grain is blended with lower quality to meet the minimum requirement for processing. In 2009, Thakur et al. analyzed a grain blending system, using a multi-objective mixed integer programming model to meet customer specifications and minimize the number of bins for food traceability reasons. They analyzed the grain system, working also to

minimize customer discounts which are given if the grain does not meet quality specifications. The model produced gave the elevator a set of blending options.

Thakur et al. (2009) stated the importance of traceability for food safety reasons as the following: “Traceability is important for many reasons such as responding to the food security threats to documenting chain of custody, documenting production practices, meeting regulatory compliance, and analyzing logistics and production costs.” In their paper, the group is working to reduce the number of bins, while still meeting the required quality specifications and not losing money from low quality discounts. Using as few bins as possible allows for greater traceability in cases of recalls or other emergencies where a particular lot is needed to be traced. Reducing the number of bins allows for easier tracking backwards through a processing system if there is a quality or other issue.

One issue with using just blending to obtain the necessary quality attributes is the assumption that the test done to determine key quality measures upon entry into the processing system is representative of the entire lot. A study done by European Food Research and Technology called the Kernel Lot Distribution Assessment (KeLDA) determined that GMO distribution is not random, meaning that normal samples taken for testing do not give a perfect portrayal of the lot, the samples showed a heterogeneous pattern when tested multiple times per lot (Paoletti et al., 2006).

Johnson (2005) realized that studies have been done for sorting and blending grain, but the quality of that grain was always known with certainty. This led to the expectation that once the grain was tested, all attributes obtained through this testing were absolute. Knowing that there was a distribution across lots and then again when blended in a system, he decided to analyze these attributes under the assumption that they not known with certainty, and then

assessed the overall quality of grain out of the system after sorting and blending. The paper then developed an optimization model which incorporates the uncertainty of quality at an overall level and how this would affect blending decisions. In this particular scenario, the goal was to obtain a certain level of protein, as certain protein will give either premiums or discounts.

Johnson noticed that this uncertainty comes from not only the initial testing of the grain going into the system, but also how the blending both within the bin as well as on output (using more than 1 bin with certain quality attributes) influence the final quality. The experiment process involved drawing six samples with a mixed normal distribution from the region they were testing. The samples were then split into a high protein group and low protein group, with 3 samples in each. This was repeated 100 times to represent the expected returns on blending given the distribution of protein within the available lots. This was compared to a simulation where the lots were not split and just pulled from randomly. In all cases, sorting the grain before entering the system increased profits.

While most blending solutions utilize integer, linear, or mixed integer programming models through specialized software and advanced control systems, we decided to analyze available data and propose a system that would not require additional plant capabilities. How the contamination percentages are segregated into BSGs is based on historical data collected for 9 different runs and the blending proportions are determined based on multiple iterations of the model, working to reduce labor inputs as much as possible. Doing this allows the plant to use their current infrastructure, not requiring the purchase of software to do the blending as well as equipment that can handle the subtle changes required by the software, such a variable frequency drives on the outlet or load cells to determine how much grain is

coming out of the system, while still utilizing the least amount of changes required for an operator to make during system production.

Materials and Methods

To model this system, we created a discrete time model using lot-by-lot contamination levels as an input, with data provided from the collaborating entity from real non-GMO runs (see Chapter 2). Upon entry into the system, the accepted lots are segregated into BSGs, determined by its contamination percentage. Each lot is assumed to have equal size. This assumption is well supported by delivery truck capacity. The model takes the contamination test data, determines if it will be accepted or rejected into the system, and if accepted, will put it in the designated bin for that particular contamination range. It then uses simple mass balance mixing approaches to track contamination levels inside the each of the bins. The output contamination going into the mill is determined using the contamination levels within each bin and calculating the contamination to the mill by the mass contamination from each bin being used in the mixture.

For purposes of this paper, acceptance threshold is the highest percent contamination allowed into the storage system. Corn entering the overall bin storage system and then segregated into BSGs will be called input. After exiting the bins to be blended and processed, the contamination level in the output from the bin storage system has to be less than 0.9 percent. Due to the complexity of the milling processing system, we decided to assume perfect blending within the BSGs, giving different contamination levels for each designated contamination range. The overall contamination to the mill is what is being measured- the terminology of ‘output’ is the product going into the mill. Third party labeling cutoff for acceptable GMO contamination percent is 0.9 percent, which is what this model will be using as its success criteria.

In order to model the storage system, we decided to utilize a discrete time model; each timestamped lot will come in sequentially, be accepted or rejected and then enter the appropriate bin if accepted. While the number of lots coming into the plant is different for each run, generally corn is accumulated for a day without being pulled into the mill processing system. After this time period, corn would still be accepted, but then lots would go to processing at the same rate. This happens for 10 days, with the last day running out the corn in the storage system without receiving new shipments. Each run has approximately 1,400 lots that come in during the 11-day period.

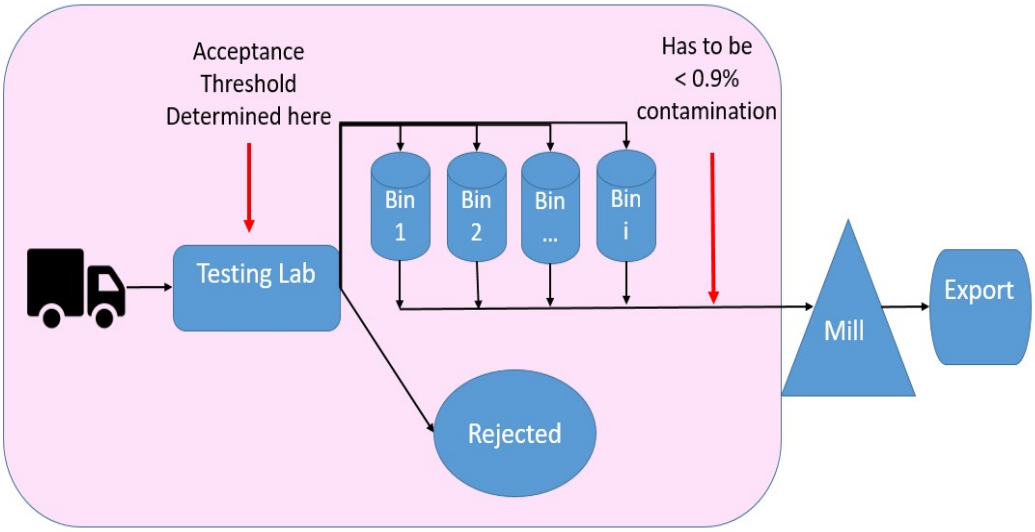

Figure 9 Overview of mill, including bin storage system with bin sub groups 1-i (central), input threshold check (left red line), output contamination level (right red line)

Figure 9 above shows the process as corn enters the storage system, to be either rejected from the process or added into a BSG. When the lots initially arrive at the processing facility, a probe is used to extract a sample from the truck to take to the testing lab to determine the percent GMO contamination of that lot. A commercially available quick test is used to determine the contamination level of each lot. The quick test involves the following

steps: (1) grind approximately a ½ gallon of corn through a 20-mesh sieve and mixed thoroughly, (2) 240-g sample is weighed out and added to a quart sized container, (3) 360 +-2ml of tap water is added and shaken vigorously for 30 seconds, (4) the sample settles for at least 30 seconds and then liquid is drawn off, (5) 20ml of the liquid portion of the settled sample is put into a sample cup and allowed to settle for 30 seconds, (6) a quick test strip is added into the sample, which develops for 5 minutes before being interpreted, and (7) the test strip is placed into the a strip reader, with results displayed on a computer.

After the contamination level is determined, the lot is either accepted or rejected based on the value of the contamination relative to an acceptance threshold value and then added to the appropriate BSG depending on the contamination value. BSGs will be denoted as BSG_i with i being the BSG from 1 to i. The contamination percentage determined by the quick test is denoted as $c_{n,}$ with n being the contamination of the lot being tested.

In this modeling work, the acceptance threshold of 2.5 percent was used, which is consistent with what the collaborating entity uses during normal non-GMO runs. Accepted corn enters the BSGs based on contamination and is comingled with the existing corn within the BSG. Mixing of the lot within each BSG happens naturally within the entire system as corn is transferred from bin to bin for processing purposes, when it is on the way to the processing system, and finally within the processing system. Due to these mixing events that are inherent to the bin storage system, we assumed perfect blending within each BSG, as well as when it is on the way to processing between the BSGs. The assumption of perfect blending implies that output contamination percentages are equal to the mass average contamination of how much each sub bin group contributes to the final output to the mill per the following equations:

$$B_i = \sum_{i=1}^{m} \frac{c_{n,i}}{BV_i}$$

(Equation 7)

Where B_i is the contamination within each BSG from 1 to m, $c_{n,i}$ is the contamination of the lot coming into specific bin subgroup i, and v_i is the total volume of BSG i.

For the first day, the contamination percentage of each BSG storage system is equal to the average of the inputs into the bins. In order to normalize the contamination added to the storage system, the following set of equations is used:

$$m_{i,curr} = m_{i,prev} + V_n \times C_n$$

(Equation 8)

$$BV_{i,curr} = BV_{i,prev} + V_n$$

(Equation 9)

$$c_i = \frac{m_i}{BV_{i,curr}}$$

(Equation 10)

where $m_{i,curr}$ is the total mass contaminated grain going to BSG i, $m_{i,prev}$ is the total mass contaminated grain already in BSG i, V_n is the volume of lot n coming into the bin system, c_n is the contamination of the lot entering the bin system, $BV_{i,curr}$ is the current volume of BSG i, $BV_{i,prev}$ is the volume of BSG i before the new lot comes in, and c_i is the contamination of each bin system assuming perfect blending.

Once this accumulation period is completed, the system starts feeding into the mill as well as accepting new lots. The output contamination going to the mill is calculated using the following equations:

$$m_{i,curr} = m_{i,prev} + V_n \times c_n - c_i \times V_{n,out}$$

(Equation 11)

$$c_i = \frac{m_{i,curr}}{BV_i}$$

(Equation 12)

$$c_{out} = \sum_{i=1}^{m} P_i \times c_i$$

(Equation 13)

The new equation for $m_{i,curr}$ accounts for the output to the mill, c_{out} is the contamination going to the mill, with P_i as the percentage of the total volume going into the mill from each BSG. As new lots are accepted into the system, the contamination changes, resulting in a new contamination output percentage. This output value was collected and analyzed to see the values going into the milling system over the entire run.

To determine how many BSGs to create for blending purposes, we first had to look at the capabilities of the system including how many bins were available to segregate into, how many bins were able to be pulled from at once to go into the mill, and capacity constraints of these bins. While all of these are important, bin number and capacity were not constraints for this plant. We decided to focus on how many bins could be pulled from at once to go to the mill. The mill pulls from bins based on the amperage lot of the mill. When the lot is too small, another bin will open up. Generally, the plant pulls from two to four bins when running their system. This was the range of BSGs we wanted to choose from

After determining the range of the number of bins to use, reducing risks of operator errors was considered. If corn was put into the incorrect bin, the contamination of that BSG would be incorrect and the advantages of blending could be lost. Due to this, 3 bins was the

correct number of bins to use. The system is set up to pull from three bins into the mill, and this reduced number allows for the plant to still benefit from blending. Three bins also kept management changes minimal once the system is properly set up and training was complete.

Next, the contamination ranges for each BSG had to be determined. To do this, the data from the 9 provided runs was compiled and grouped based on contamination percentage. Each group had a range of 0.1 percent, with everything 2.5 percent and above being counted together. Two and one-half percent contamination was chosen as the upper limit because that is generally the upper acceptance threshold the plant uses. Figure 2 in Chapter 2 shows a histogram of all the available data. This graph shows approximately 40 percent of the total lots tested had 0 percent contamination. Because of this, we decided make BSG1 accept lots tested for 0 percent contamination. To better understand the divisions excluding the 0 percent contamination lots, the data was analyzed taking these lots out to produce the following graph:

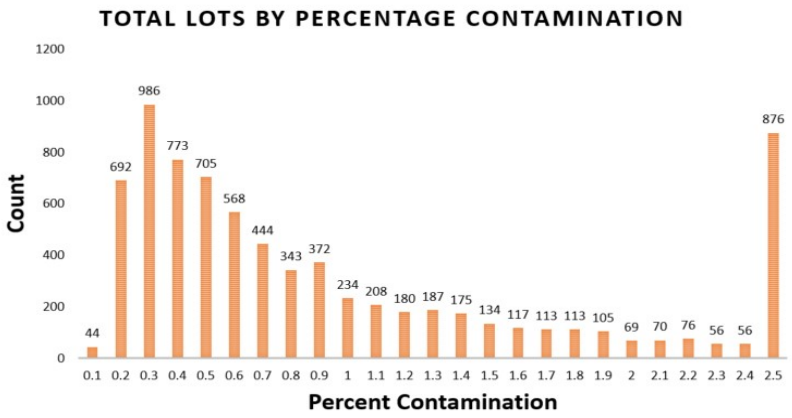

Figure 10 Distribution of lots entering the system over 9 runs, split into contamination values, excluding 0 percent contamination

From this analysis, it was difficult to decide on the range of the last two bins. The remaining lots accounted for around 60 percent of the lots into the system. We wanted the

opportunity to slowly blend in the bin with higher contamination corn. Doing this reduces the risk of running into a ‘hot spot’ of this highly contaminated corn. Hot spots are when the corn is not blended properly and a highly contaminated BSGs is processed, leading to an output product higher than the final quality standard of 0.9 percent contamination level. Currently, the upper acceptance threshold into the plant is not fixed and changes from 2 to 2.5 percent contamination, depending on what is already in the system. Because of this, as well as the desire to blend in the high contamination bin slowly, we decided to make the range of BSG2 0.1 to 1.9 percent contamination and BSG3 accepting lots testing 2.0 percent acceptance threshold.

After determining the contamination ranges for each BSG, determining how much of each range to send to the mill needed to be decided. We did not want the percentages to be too specific. The capability of the plant, including the resolution of the outlet valves on the bins, does not allow for exact percentage ratios to the mill. We decided to keep the percentages imprecise, running simulations based on the overall quantity going into each bin with the ranges determined above: 40 percent from BSG1, 50 percent from BSG2, and 10 percent from BSG3 into the overall mix going into the mill. The following table summarizes the ranges and quantity going to the mill for each bin level:

Table 5 Summary of bin sub group contamination range and percent of each bin sub group going to the mill under normal conditions

BSG	Lower Limit	Upper Limit	% of total lot
BSG1	0%	None	40%
BSG2	0.1%	1.9%	50%
BSG3	2.0%	Upper Acceptance Threshold	10%

As the percentages above are for based on all the data we have available, we had to determine what to do if any of the bins became empty or low during the simulation of a particular run. Quantities that go into each bin change with each run, and because we are using time-stamped data, a particular BSG could become empty or low. Then, sufficient volume could be added later in the run as lots come into the system. Each BSG requires a different solution for what to do if a shortage occurs. Because the capabilities of the mill are limited, we wanted to run the simulation to reflect how the operators would react if a bin was getting low. Shutting down and starting a mill is difficult to do, so continuing to run even with grain shortages is required. To give the plant guidance on what to do in the instance a BSG does get low or empty, we created the following decision tree:

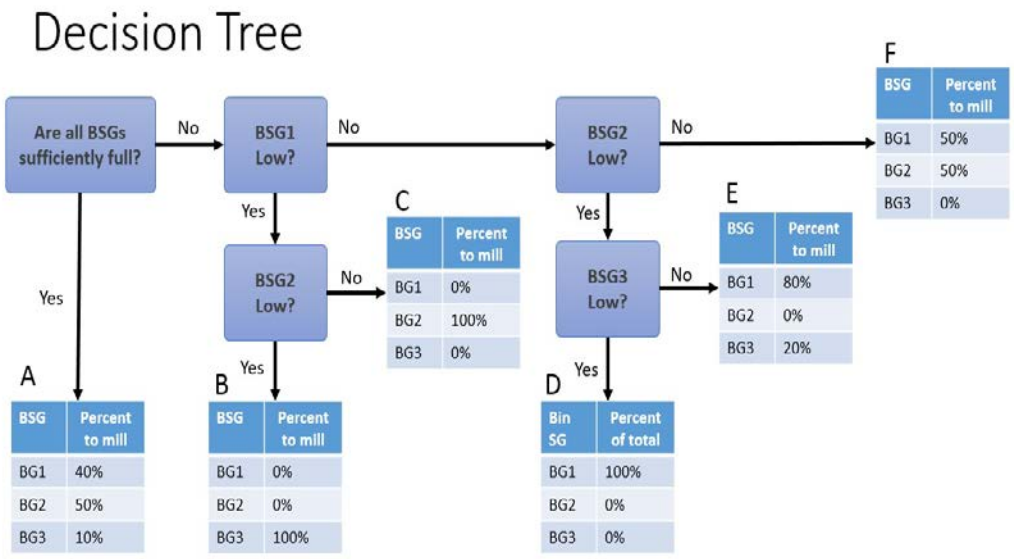

Figure 11 Decision tree for what to do when any of the bin sub groups runs low or empty. Normally utilized at the end of a run

The decision tree is broken up into what happens if any of the bins are empty. Table A describes the instance in which bins are sufficiently full (normal state). The percent of each BSG going to the mill is what was determined above to be the steady state of the mill. When not in steady-state, we first look at if BSG1 (the group with 0% contamination) is empty. For this instance, we first need to check if BSG2 is empty or low. If not, then we decided to just change completely over to BSG2 (table C). This can be risky as running into a high contamination spot if blending within the group is not done properly, however, the average contamination of BSG2 with all data included is 0.7%, below the 0.9% requirement. Most likely, the product coming only from BSG2 would be sufficient for quality. If BSG2 is also low, the mill will most likely go to BSG3 to avoid a shutdown (table B). In this instance, the plant will have to collect the product during this time frame and send it as export as a non-GMO product as it will be above the 0.9% threshold (table B). The likelihood of going to table B is low and during no point in the simulations did this happen.

If BSG1 is sufficient, we will then check BSG2. If this one is low or empty, we will first look to see if BSG3 is also low or empty. If it is, we will switch completely over to BSG1 (table D). Doing this is expensive as we are running the purest corn which costs the most. Without BSG2, there is more potential to use the BSG3 as it will be mixing with the 0% contamination corn in BSG1. If BSG3 is available to use, we decided to utilize more of it and save money on the output to the mill. In this case, we will run the simulation with 20% BSG3 and 80% BSG1 (table E).

The last scenario we will run into is if BSG3 is empty with the other bin groups still sufficiently full. To simplify this process, each will send equal amounts of corn to the mill (table F) resulting in a contamination percentage of the average of BSG1 and BSG2.

Once we had the simulation set up to run properly with a 2.5% acceptance threshold, we wanted to determine if we could change this upper acceptance threshold to accept cheaper corn into the system. Normally, the plant runs this to 2.0%-2.5%, depending on what is coming into the system. If the plant is receiving higher contaminated corn, they will reduce the acceptance threshold to 2.0%, but if they are getting a low average contamination, the acceptance threshold is 2.5%. This is primarily done as a safety net in case there are sections of highly contaminated corn which haven’t been blended throughout the system. However, the proposal of three segregated bins slowly blends in the higher contaminated corn, greatly reducing the likelihood of running into one of these hot spots.

To test how changing the upper threshold would affect the output of the system, we ran the simulation to include upper acceptance thresholds ranging from 2.0%-10.0% in 0.25% increments. The overall average contamination going to the mill was recorded, as well as the number of lots that were rejected at the testing lab.

We also wanted to run other scenarios not provided in the data sets to help the plant make decisions on how to run if the average or variance of the lots coming in is vastly different than those of historical runs. We created random data sets in MATLAB using a range of Beta parameters which spanned the means and standard deviations given to us by the data sets provided by the collaborating entity. We ran these through the simulation to predict under what scenarios the plant could be running into potential issues with meeting the 0.9% contamination criteria.

Data

Some of the simulations used data from the collaborating entity identical to those described in Chapter 2. However, to challenge the system, we also generate sample artificial data sets which are statistically similar to the actual data provided by the collaborating entity, but which have more extreme contamination. As detailed in Chapter 2, a number of phenomena give rise to varying levels of contamination in the feed coming to a real mill. In this work, a collaborating entity provided 9 data sets taken from a 15-month period beginning in August 2017. After examining several possible statistical distributions of the data, a beta distribution was selected for describing these data, and MATLAB functions were used to determine parameters alpha and beta associated with each of the nine data sets provided. Table 6 below (also in Chapter 2) summarizes the results of this fitting exercise.

Table 6 Data sets used in simulation model

Data Set	Total lots	Rejected lots	Average Contamination	Standard Deviation	Alpha parameter	Beta parameter
1	1294	77	0.56	0.93	0.27	39
2	1108	112	0.71	1.21	0.31	35
3	1254	309	0.83	0.69	0.46	27
4	1710	155	0.42	0.58	0.25	39
5	1468	128	0.46	0.59	0.26	40
6	1698	69	0.4	0.51	0.27	53
7	1537	104	0.47	0.57	0.28	43
8	1460	55	0.38	0.52	0.26	55
9	1400	68	0.37	0.51	0.25	47

From the above data sets, we chose to analyze the lowest contamination average (set 8, hereby low contamination) and a normal contamination average (set 5, hereby average contamination). These two runs were analyzed to determine if splitting into three sub groups as well as changing acceptance threshold would be beneficial for all of the runs or if management would be required to ensure the proper quality going into the mill.

We also created our own data sets using, utilizing alpha and beta parameters which spanned the data sets provided. A best fit line from the relationship between alpha and beta above was used to determine a corresponding value of beta for a set alpha parameter, and MATLAB's *betarnd* (Mathworks, 2006) function was used to create the sets. We created 65 of these data sets, each with 1400 values.

Comparison to how system currently runs

This work follows up on a previous simulation which analyzes the system without splitting into BSGs. The work done before assumes perfect blending within overall bin system, allowing the output into the mill to be characterized by the average contamination within the entire system. While the old simulation gives a good rule of thumb for what the contamination of the system is as a whole, the risk of running into a ‘hot spot’, leading to an output to the mill greater than the necessary 0.9% contamination average. The benefit of splitting the bins into BSGs allows for greater control of this risk, potentially allowing the system to accept even higher contamination levels than those currently being accepted.

The risk of using a system like this is the requirement for extra management as the system is being introduced as well as when the contamination levels are skewed from those represented by our model. When the system is first introduced, making sure operators know which bins belong to which BSG and then ensuring the grain goes to the correct BSG will require additional training. There is also a risk of having contamination ranges be different than those ran in the simulation, potentially requiring different percentages of each BSG going into the final output to the mill. In this instance, management will need to be aware of approximate contamination percentage in each BSG and adjust these outputs accordingly, while still being able to be confident in not going above the 0.9% contamination requirement.

The results below show not only what the simulation with 3 BSGs accomplishes, but compares these numbers to the single bin group system as well.

Results

Running the simulation with the selected two sets of data, results in the following averages going into the mill:

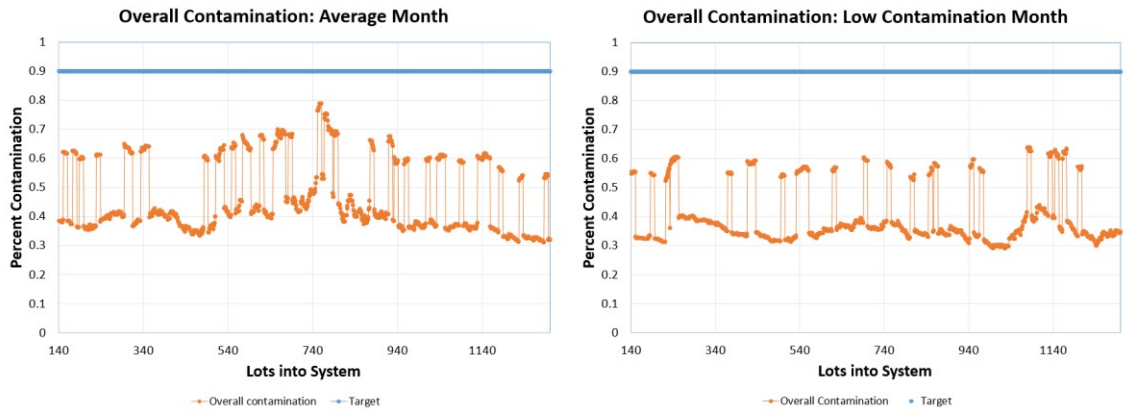

Figure 12 Contamination going into the mill from a 3 bin system for average and low contamination runs

The peaks in both simulations are a result of the BSG3 coming into the system; the lower contaminations happen when BSG3 is empty. The following table summarizes the characteristics of the simulated runs:

Table 7 Statistical summary of low and average runs through the simulation model

Run	Avg. Contamination %	Standard Deviation	Max Contamination %
Average	0.452%	0.122%	0.788%
Low	0.394%	0.0967%	.639%

As can be seen above, the potential to accept higher contaminated corn is possible, especially if it is slowly entered into the system. In order to test including more highly contaminated corn, we decided to run the system with acceptance thresholds ranging from

2.25 to 10 percent, allowing us to see if accepting the lots that are normally rejected could be included in the production run without risk of going above the 0.9 percent required threshold. We ran the simulation a total of 40 times, changing the acceptance threshold in 0.25 percent increments, starting at 2.25 percent and going to 10 percent. During these simulations, the mean contamination into the mill, as well as the number of rejected lots due to this changing threshold were collected. The following graphs show the results for both the low and average contamination runs:

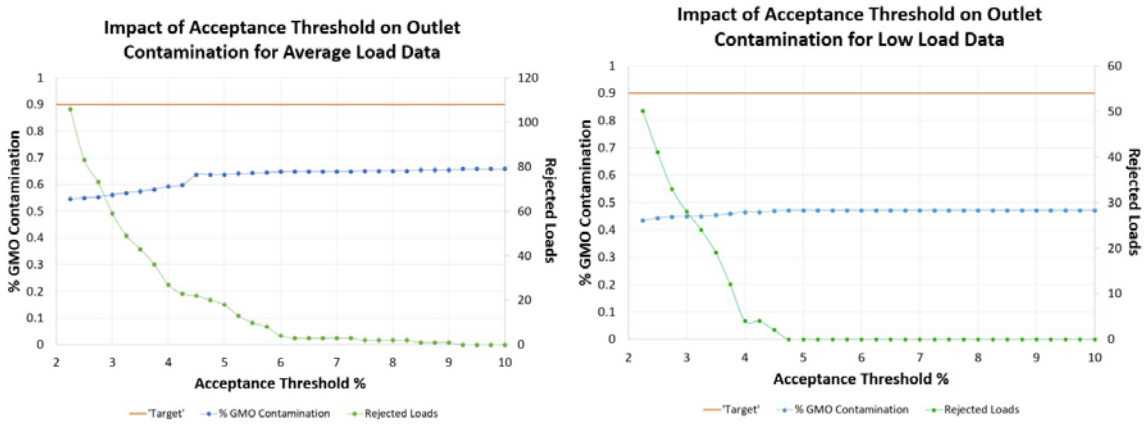

Figure 13 Average contamination going to the mill with changing acceptance thresholds for average and low contamination runs

Raising the acceptance threshold, even to be feeding in 10.0 percent contamination keeps the average going into the mill below the 0.9 percent contamination requirement. The ability to accept higher contaminated corn and slowly bleed it into the system reduces the number of rejected lots, giving an outlet for corn historically rejected from process. The system can also run at a cheaper price per lot out as less pure corn is usually bought for a lower price than higher quality corn.

One potential issue with the simulations above is that the scope is rather limited. The data given by the collaborating entity has a small range of divergence and does not give the plant a plan forward if the contamination average is coming in higher or with more variation. Due to this, we decided to run the system for a range of beta parameters, which produce different means and standard deviations.

We first took the data sets given to us by the collaborating entity and used Matlab's *fitdist* function to determine the beta parameters for the given data. After this, we graphed the alpha and beta parameters and used a best fit line to determine the relationship between the two using Excel. We obtained a best fit line of $y = -90.882x + 68.372$, with a R^2 value of 0.469. With this information, we created a function in Matlab which used alpha values from 0.2 to 0.52 in 0.01 increments, calculated the corresponding beta parameter using the best fit line equation above, and then created random data sets using MATLAB's *betarnd* function (Mathworks, 2006). This created 65 data sets which were then ran through both the 1 BSG and 3 BSG simulation model.

To compare the generated data sets with the real data sets, the following figures show a generated set next to real data with similar beta and alpha values. We used data set 7 from Table 6 above to compare as the best fit line gave the closest values for alpha and beta from this set. Data set 7 had an alpha parameter of 0.28 and a beta parameter of 43, while the set compared has an alpha of 0.28 and a beta of 44.8. Figure 14 shows the probability distribution function of both of these data sets:

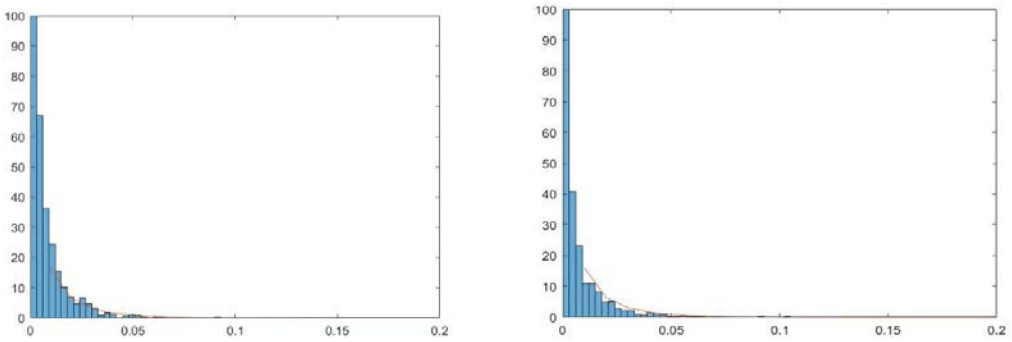

Figure 14: Left, Probably Distribution Function for Data set 7, Right, Probability Distribution Function for random data set with alpha 0.28, beta 44.8

The simulation results were surprising. We ran the multiple data set simulation for both the current system, for the original 1 BSG system, as well as for the proposed 3 BSG system. The simulation was ran at a 2.5 percent acceptance threshold, with 1,400 incoming lots. The ratio of how often the output to the mill was higher than the 0.9 percent contamination threshold for each created data set was evaluated. The following graph shows how the systems responded to the same data sets coming in, with a range of means and standard deviations determined by the beta parameters:

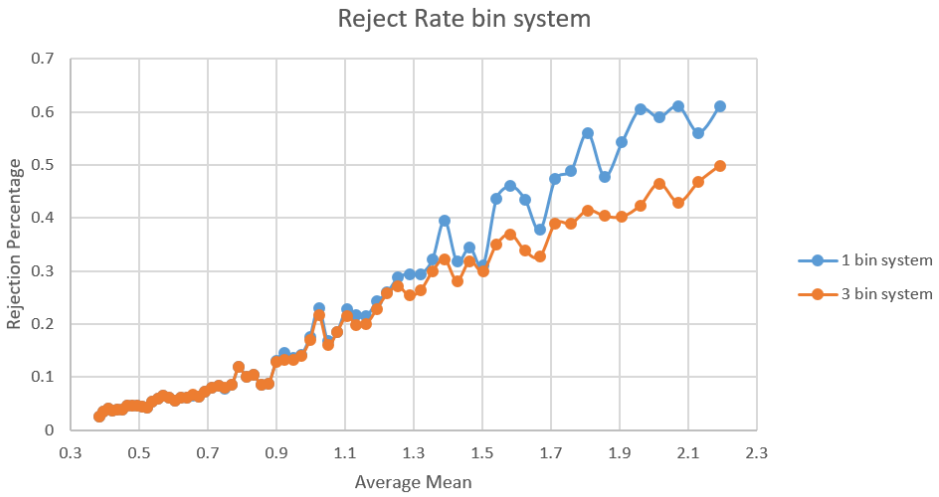

Figure 15: Rejected load percentage as mean increases in 1 and 3 bin systems

As can be seen, the simulated data rejected about the same amount for the 1 and 3 BSG systems until around a 1.0 percent average coming in. After that, the 3 bin system shows for less rejections going into the mill.

Segregation based on contamination not only increases confidence in the output to the mill due to how the high contaminated corn is fed into the system, but the plant is also able to better track where particular lots are in cases of recall or other quality issues. We decided on 3 BSGs, but other plants with more capability could utilize more to increase this confidence as well as blending potential. With how much lower the overall contamination was into the mill than the requirement, it would be interesting in future work to see if the plant could accept even higher contaminated corn than it is currently doing. The 2 BSG system not only allows for more confidence in producing what is needed even through higher mean and greater variance lots coming in, but reduced the potential for hot spots throughout the system.

Future labeling laws in the United States, allowing up to 5% GMO contamination, could mean a new market, especially considering the purity of what is currently coming into the system. The collaborating entity would be able to accept much higher corn, potentially working with farmers on contracting options which could be beneficial to both the collaborating entity and the farmers they buy from. Future work could be done on this to assess the impacts of the new law, as well as how it could affect farmers in Iowa.

Conclusion

In this paper, we made a decision model which chose how many bin sub groups this particular non-GMO grain processing system should utilize, as well as the GMO contamination range of bin sub group and the percentage of each in the final flow into the mill. In addition, we also created a decision document to describe what should happen in the event any of these bin sub groups ran low or empty during processing.

In order to check the validity of our decisions, we simulated multiple runs using a discrete time model, using historical time stamped data from the collaborating entity and analyzed the output contamination to the mill. We evaluated increasing acceptance threshold, allowing higher contaminated lots into the system to reduce the costs of production.

We then compared the average contamination going into the mill as well as the number of rejected lots of the proposed 3 bin sub group system with current processing system, which does not utilize segregation based on contamination. We also simulated potential future runs using random data with ranges of standard deviation and means to understand differences in these two systems. While the decisions made in this paper are for this particular system, the decision making exercise used here could be used for other grain processing systems, as well as applied to other quality metrics such as moisture and protein content.

CHAPTER 4. GENERAL CONCLUSION

This work is especially useful for future food markets as new labeling laws in the United States will most likely require an increasing amount of non-GMO corn production. The new standards allow for more leeway for contamination, potentially opening a category for producers to create new market segments to fit within the new criteria all while utilizing the maximum amount of non-GMO corn grown.

Future work in this area could include a more comprehensive grain blending model to fully understand what is in the system, potentially realizing even more ability to add in higher contaminated corn. The ability to split the system into the current standard (0.9 percent and below), and what will soon be required for USDA laws (5.0 percent and below) could allow for even more bin sub groups to be utilized, reducing costs per lot out of the system.

Another interesting set of potential work could include looking at contract negotiations with farmers. Currently, farmers are paid premiums for the purity of each lot- the higher the purity, the higher the premium paid to them. Growing non-GMO crops is risky due to the high risk of contamination from cross pollination as well as the supply chain to the production company. With the new USDA labeling laws allowing a much higher contamination level, allowing farmers to bring in these higher contamination lots and still run them as non-GMO corn would bring a new category of premiums, potentially incentivizing more farmers to grow non-GMO crops without the risk of not earning a premium.

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